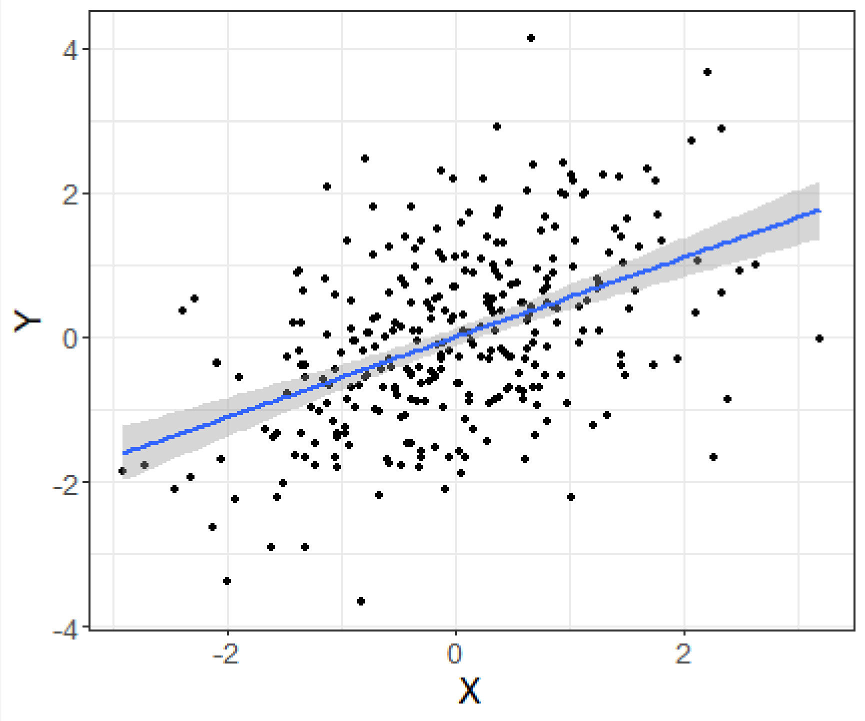
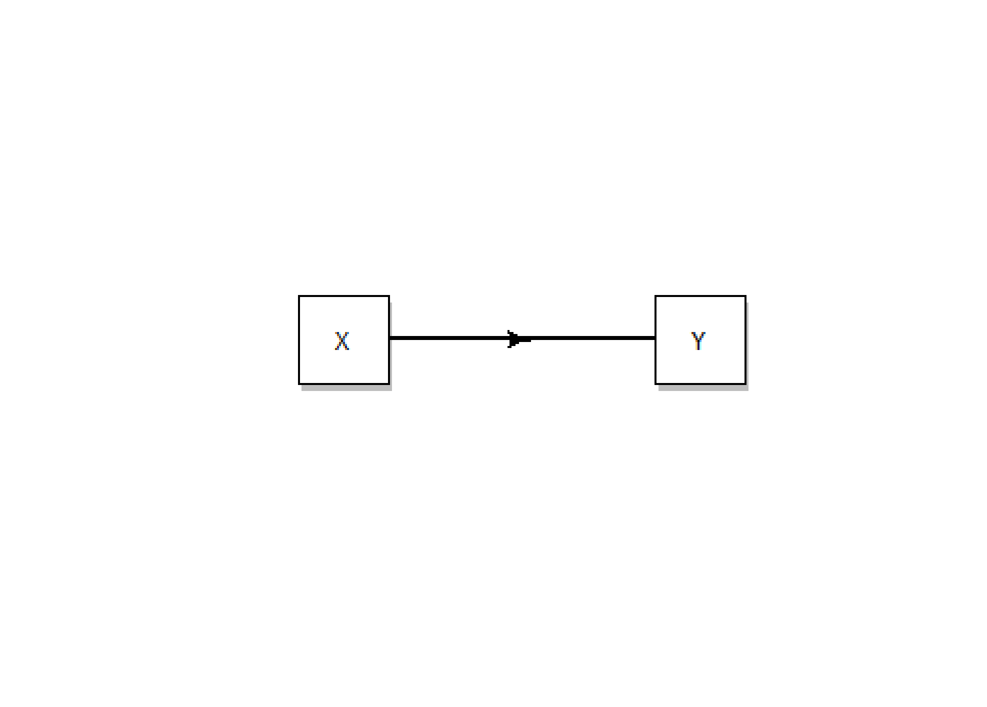
Moderation and Mediation

2022/05/03

Mediation and moderation

In linear regression, we're looking to understand the relationship between *predictors* and *outcomes*.

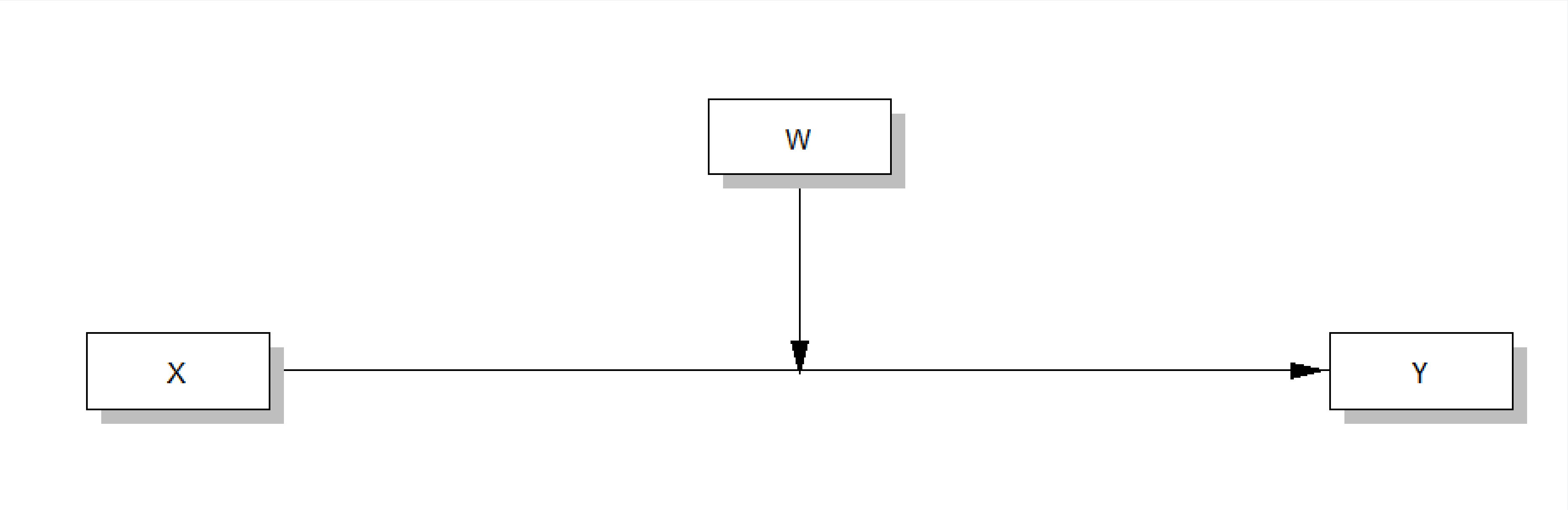




Moderation

Moderation

Moderation is when the strength of the relationship between two variables depends on a third variable.



The *epi.bfi* dataset

The `epi.bfi` dataset from the `psychTools` package

```
head(epi.bfi)
```

```
##   epiE epiS epiImp epilie epiNeur bfagree bfcon bfext bfneur bfopen
## 1   18   10      7      3       9     138    96   141     51    138
## 2   16    8      5      1      12     101    99   107    116    132
## 3    6    1      3      2       5     143   118    38     68     90
## 4   12    6      4      3      15     104   106    64    114    101
## 5   14    6      5      3       2     115   102   103     86    118
## 6    6    4      2      5      15     110   113    61     54    149
##   bdi traitanx stateanx
## 1   1       24       22
## 2   7       41       40
## 3   4       37       44
## 4   8       54       40
## 5   8       39       67
## 6   5       51       38
```

Simple linear regression

Let's model `bdi` (Beck Depression Inventory) as a function of `stateanx` (State Anxiety)

```
st_bdi <- lm(bdi ~ stateanx, data = epi.bfi)
summary(st_bdi)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx, data = epi.bfi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.1115  -3.0603  -0.6826   2.2152  15.1130
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.41988    1.09322  -4.958 1.39e-06 ***
## stateanx     0.30614    0.02637  11.611  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Multiple linear regression

An additional predictor that we may find interesting is `epiNeur` - a measure of *neuroticism* from the *Eysenck Personality Inventory*.

```
st_neu <- lm(bdi ~ stateanx + epiNeur, data = epi.bfi)
summary(st_neu)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx + epiNeur, data = epi.bfi)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.7405 -2.5748 -0.5299  2.2841 11.7303
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -6.32655    1.01061  -6.260 1.89e-09 ***
## stateanx     0.21526    0.02770   7.770 2.66e-13 ***
## epiNeur      0.43492    0.06493   6.698 1.63e-10 ***
## ---
```

Adding interaction terms

What if the effect of `stateanx` depends on the level of `epiNeur`? For example, people who score high on *neuroticism* might be more affected by *state anxiety* than people who are low on *neuroticism*.

We add an interaction to our model using `:` between the two variables:

```
int_model <- lm(bdi ~ stateanx + epiNeur + stateanx:epiNeur,
                data = epi.bfi)
```

We can also use `*` instead of `+`. Thus, `stateanx * epiNeur` will give us the main effect of `stateanx`, the main effect of `epiNeur`, and the interaction between the two.

Moderation

```r
summary(int_model)
```

```
##
## Call:
## lm(formula = bdi ~ stateanx + epiNeur + stateanx:epiNeur, data = epi.bfi)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.0493  -2.2513  -0.4707   2.1135  11.9949
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.06367    2.18559   0.029   0.9768
## stateanx          0.03750    0.06062   0.619   0.5368
## epiNeur          -0.14765    0.18869  -0.782   0.4347
## stateanx:epiNeur  0.01528    0.00466   3.279   0.0012 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.12 on 227 degrees of freedom
## Multiple R-squared:  0.4978,    Adjusted R-squared:  0.4912
## F-statistic: 75.02 on 3 and 227 DF,  p-value: < 2.2e-16
```

Interpreting the coefficients

```
coef(int_model)
```

```
##      (Intercept)         stateanx          epiNeur stateanx:epiNeur 
##       0.06367327       0.03750035      -0.14764857       0.01527977
```

The coefficients tell you what the effect of a 1 unit increase in the variable has on the dependent variable.

But the coefficients of the main effects (`stateanx` and `epiNeur`) are hard to interpret *in the presence of an interaction* unless the variables have been **centred**.

Interpreting the coefficients

```
coef(int_model)
```

```
##       (Intercept)          stateanx           epiNeur stateanx:epiNeur 
##        0.06367327        0.03750035       -0.14764857       0.01527977 
```

When the predictors are uncentred, these coefficients tell us (*take a deep breath*)

- the effect of a 1 unit increase in `stateanx` when `epiNeur` is 0
- the effect of a 1 unit increase in `epiNeur` when `stateanx` is 0
- the difference between the effect of a 1 unit increase in `stateanx` when `epiNeur` is 0 and the increase in `stateanx` when `epiNeur` is 1, and the difference between the effect of a 1 unit the increase in `epiNeur` when `stateanx` is 0 and the increase in `epiNeur` when `stateanx` is 1

(or something like that)

Mean-centring

We can use the `scale()` function to perform mean-centring, standardization, or both.

```
cent_model <- lm(bdi ~ scale(stateanx, scale = FALSE) * scale(epiNeur, scale = FALSE),
                 data = epi.bfi)
coef(cent_model)
```

```
##                                                                (Intercept)
##                                                                 6.35996006
##                                             scale(stateanx, scale = FALSE)
##                                                                 0.19658197
##                                              scale(epiNeur, scale = FALSE)
##                                                                 0.46122726
## scale(stateanx, scale = FALSE):scale(epiNeur, scale = FALSE)
##                                                                 0.01527977
```

```
coef(st_neu)
```

```
## (Intercept)    stateanx     epiNeur
##  -6.3265496   0.2152590   0.4349163
```

```
tab_model(st_neu, int_model)
```

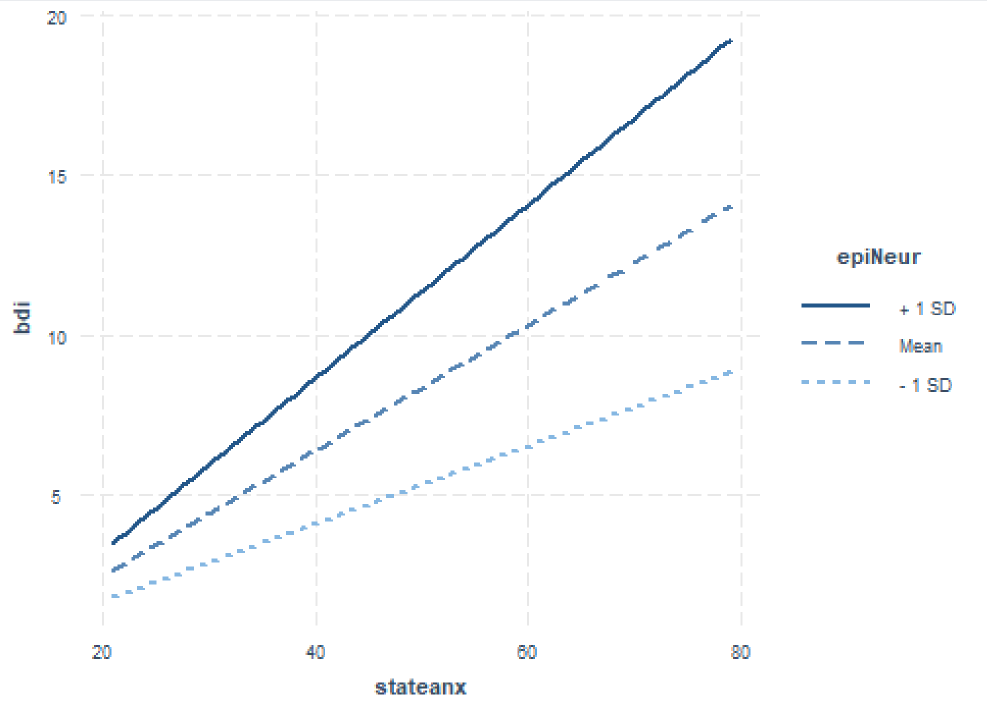
	bdi			bdi		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-6.33	-8.32 – -4.34	**<0.001**	0.06	-4.24 – 4.37	0.977
stateanx	0.22	0.16 – 0.27	**<0.001**	0.04	-0.08 – 0.16	0.537
epiNeur	0.43	0.31 – 0.56	**<0.001**	-0.15	-0.52 – 0.22	0.435
stateanx * epiNeur				0.02	0.01 – 0.02	**0.001**
Observations	231			231		
R^2 / R^2 adjusted	0.474 / 0.469			0.498 / 0.491		

Simple slopes

The `interact_plot()` function from the `interactions` package provides a nice way to visualize the interaction.

We look at the steepness of the slope at different levels of one of the variables.

```
interact_plot(int_model,
              pred = stateanx,
              modx = epiNeur)
```

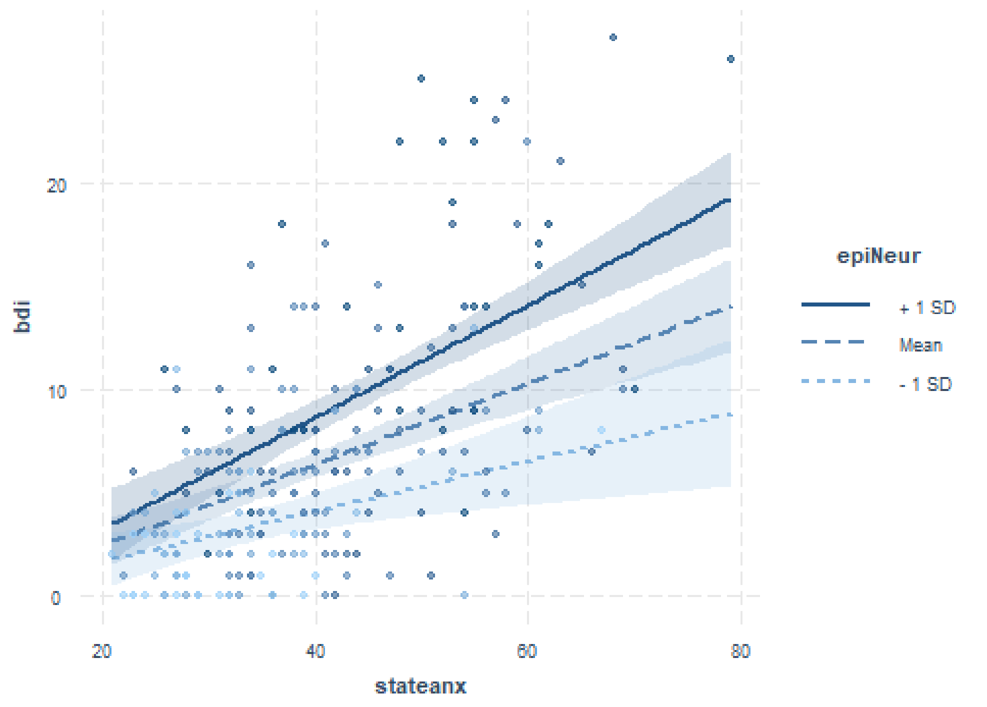


Simple slopes

We can also add individual data points using `plot.points = TRUE`.

Confidence intervals can be added using `interval = TRUE`.

```
interact_plot(int_model,
              pred = stateanx,
              modx = epiNeur,
              plot.points = TRUE,
              interval = TRUE)
```



Simple slopes

The interaction means that the *slope* of the effect of `stateanx` differs at different values of `epiNeur`.

We can use the `sim_slopes()` function from `interactions` to statistically explore how `stateanx` varies as a function of `epiNeur`.

```
sim_slopes(int_model,
           pred = stateanx,
           modx = epiNeur,
           johnson_neyman = FALSE)
```

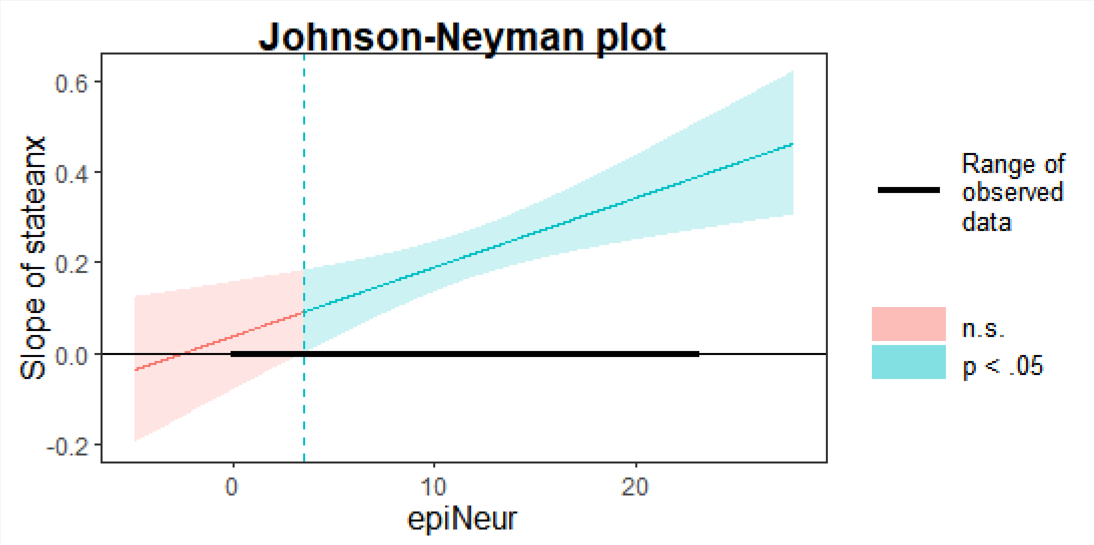
```
## SIMPLE SLOPES ANALYSIS
##
## Slope of stateanx when epiNeur =  5.511419 (- 1 SD):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.12   0.04     3.09   0.00
##
## Slope of stateanx when epiNeur = 10.411255 (Mean):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.20   0.03     7.09   0.00
##
## Slope of stateanx when epiNeur = 15.311092 (+ 1 SD):
##
##   Est.   S.E.   t val.      p
## ------ ------ -------- ------
##   0.27   0.03     8.46   0.00
```

The slope of `stateanx` *increases* as `epiNeur` increases.

Johnson-Neyman plots

```
johnson_neyman(int_model, pred = stateanx, modx = epiNeur)
```

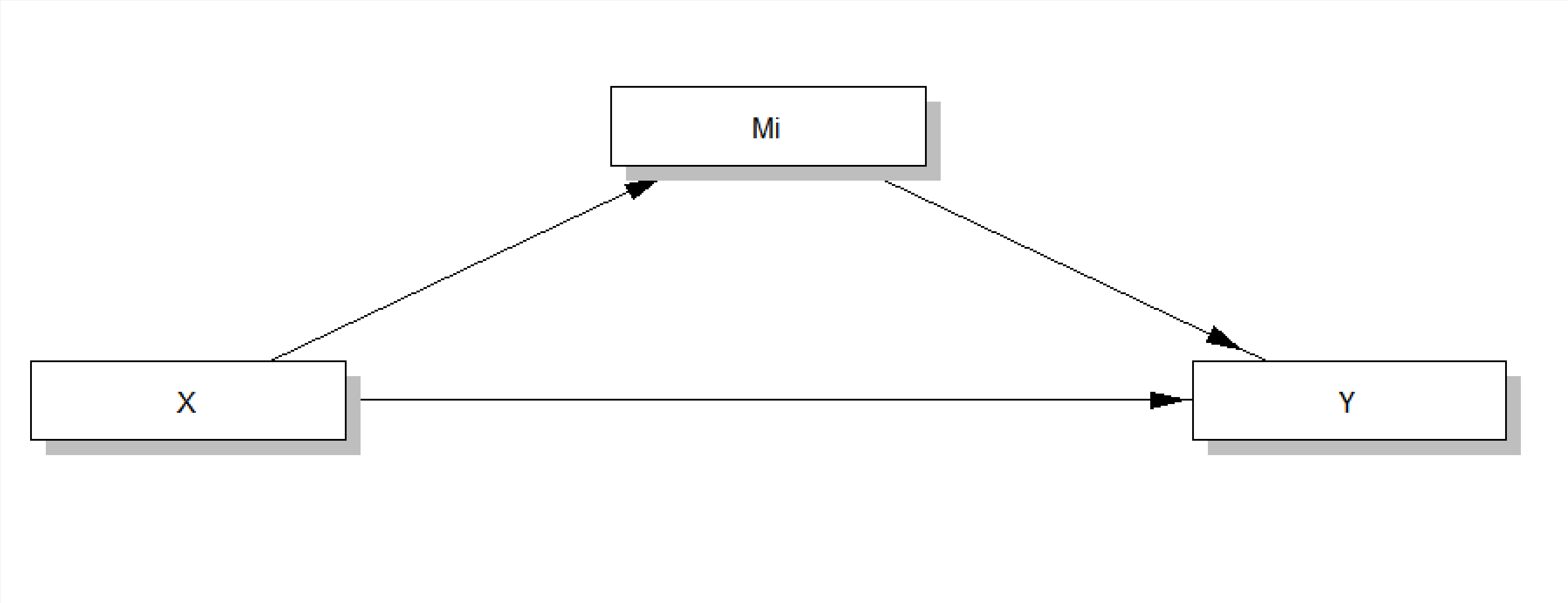
```
## JOHNSON-NEYMAN INTERVAL
##
## When epiNeur is OUTSIDE the interval [-24.37, 3.54], the slope of
## stateanx is p < .05.
##
## Note: The range of observed values of epiNeur is [0.00, 23.00]
```



Mediation

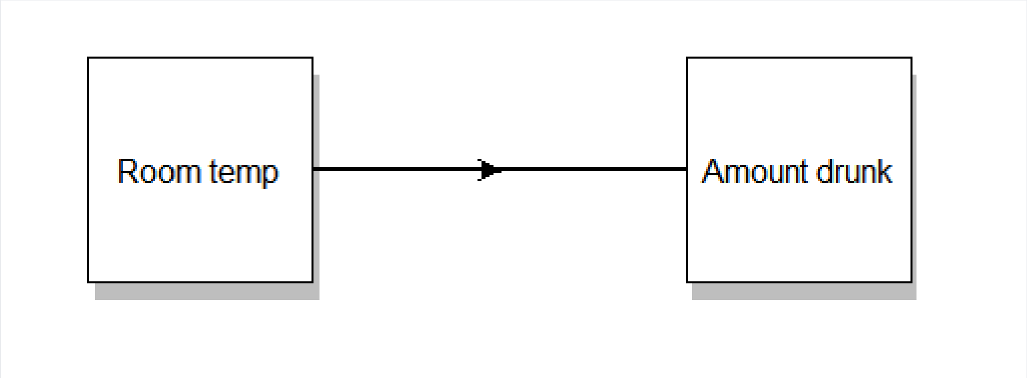
Mediation

Mediation refers to a situation in which the effect of a predictor is transmitted *through* another variable.



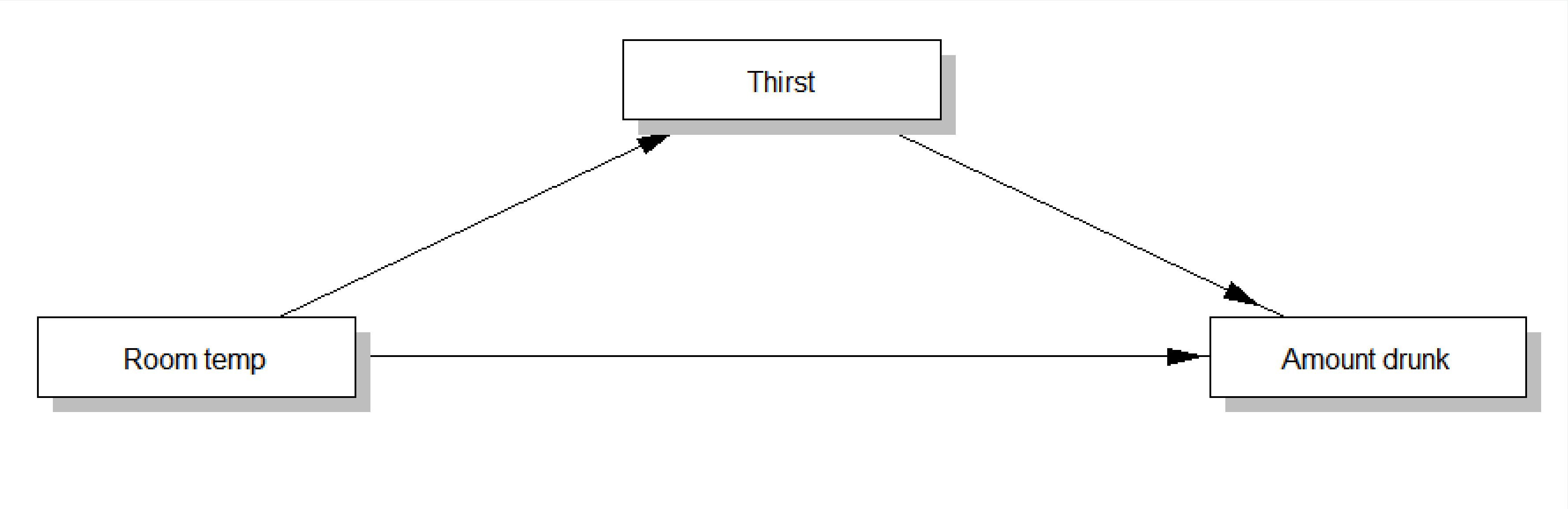
Mediation

In this example, *room temperature* predicts the *amount that people drink*; specifically, we'd expect that higher temperatures would increase drinking.



Mediation

Nevertheless, it's possible that higher temperatures increase drinking *indirectly*: higher temperatures make people feel more *thirsty*, which in turn makes them *drink more*.



Mediation path diagram

Mediation as regression

Baron & Kenny (1986) outline steps to estimate each *path* with regression.

The `estress` data

```
## # A tibble: 5 x 7
##   tenure estress affect withdraw   sex   age   ese
##    <dbl>   <dbl>  <dbl>    <dbl> <dbl> <dbl> <dbl>
## 1   1.67     6     2.6      3        1    51  5.33
## 2   0.58     5     1        1        0    45  6.05
## 3   0.58     5.5   2.4      3.66     1    42  5.26
## 4   2        3     1.16     4.66     1    50  4.35
## 5   5        4.5   1        4.33     1    48  4.86
```

Pollack, J., VanEpps, E. M., & Hayes, A. F. (2012). The moderating role of social ties on entrepreneurs' depressed affect and withdrawal intentions in response to economic stress. Journal of Organizational Behavior, 33, 789-810.

Path *c* - the *total* effect

This is the effect of the IV on the DV.

```
path_c <- lm(withdraw ~ estress, data = estress)
summary(path_c)
```

```
##
## Call:
## lm(formula = withdraw ~ estress, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4547 -1.2302 -0.2022  0.7978  4.8820
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.06187    0.26202   7.869 9.64e-14 ***
## estress      0.05612    0.05421   1.035    0.302
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Path *a*

This is the effect of the IV on the Mediator.

```
path_a <- lm(affect ~ estress, data = estress)
summary(path_a)
```

```
##
## Call:
## lm(formula = affect ~ estress, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.0095 -0.4195 -0.1609  0.2498  4.0278
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.79936    0.14331   5.578 6.11e-08 ***
## estress      0.17288    0.02965   5.831 1.63e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Path *b*

This is the effect of the mediator on the DV, controlling for the IV.

```
path_b <- lm(withdraw ~ affect, data = estress)
summary(path_b)
```

```
##
## Call:
## lm(formula = withdraw ~ affect, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1028 -0.8919 -0.2092  0.8713  2.8713
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.17416    0.17035   6.893 4.13e-11 ***
## affect       0.71772    0.09713   7.389 2.02e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

Path c' - the direct effect

This checks whether the IV predicts the DV after controlling for the mediator.

```
path_c_dir <- lm(withdraw ~ affect + estress, data = estress)
summary(path_c_dir)
```

```
##
## Call:
## lm(formula = withdraw ~ affect + estress, data = estress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1716 -0.9472 -0.2249  0.8490  2.9049
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.44706    0.25201   5.742 2.61e-08 ***
## affect       0.76913    0.10306   7.463 1.29e-12 ***
## estress     -0.07685    0.05239  -1.467    0.144
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Is there mediation?

Now that we've fit all these models, how do we work out if there is *mediation*?

Does the effect of `estress` differ after controlling for `affect`?

```
tab_model(path_c, path_c_dir)
```

	withdraw			withdraw		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	2.06	1.55 – 2.58	**<0.001**	1.45	0.95 – 1.94	**<0.001**
estress	0.06	-0.05 – 0.16	0.302	-0.08	-0.18 – 0.03	0.144
affect				0.77	0.57 – 0.97	**<0.001**
Observations	262			262		
R^2 / R^2 adjusted	0.004 / 0.000			0.180 / 0.174		

Is there mediation?

We need to calculate the *indirect* effect. There are two ways to do that.

Difference method | Product method | Which one to use?

```
coef(path_c)["estress"] - coef(path_c_dir)["estress"]
```

```
##   estress
## 0.1329641
```

Is there mediation?

We need to calculate the *indirect* effect. There are two ways to do that.

Difference method | **Product method** | Which one to use?

```
coef(path_a)["estress"] * coef(path_c_dir)["affect"]
```

```
##   estress
## 0.1329641
```

Is there mediation?

We need to calculate the *indirect* effect. There are two ways to do that.

Difference method | Product method | **Which one to use?**

Is there a mediation?

```
coef(path_c)["estress"] - coef(path_c_dir)["estress"]
```

```
##   estress
## 0.1329641
```

Calculating the indirect effect is simple enough - it looks like there is some effect of `estress` transmitted, so we may well have mediation.

But we still need to test if this is *significant*.

- The Sobel test (don't use this)
- Bootstrapping (use this)

Bootstrapping

Bootstrapping is a non-parametric resampling method.

The data is *resampled with replacement* many times over, and the test statistic is calculated each time.

For mediation, the statistic that's calculated each time is the *indirect effect*.

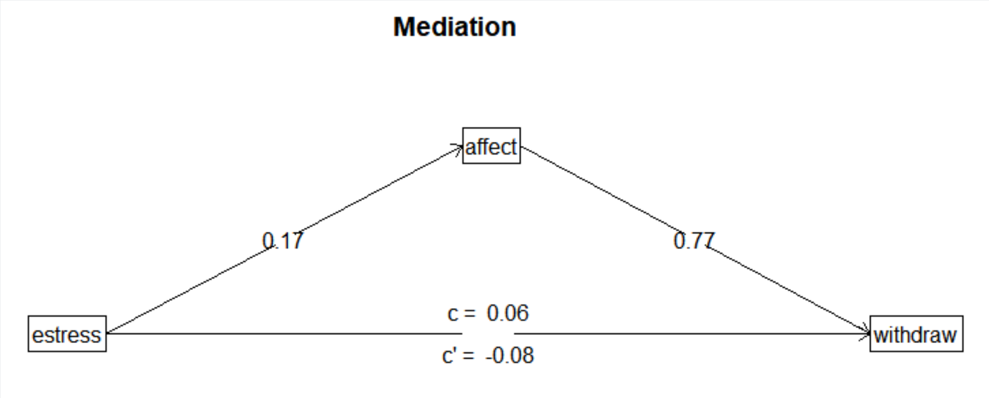
This creates a *distribution* of possible values for the test statistic, from which we can calculate *confidence intervals*.

(this is what the PROCESS macro in SPSS does)

Mediation model

We can use the `mediate()` function from the `psych` package to add a mediating variable. **Importantly,** we place `()` around the mediator.

```
medi_model <- mediate(withdraw ~ estress +
                      data = estress)
```



We can use the difference between c' and c as the *indirect* effect, so the *indirect effect* of `estress` is around **.14**.

When `estress` increases by 1, `affect` increases by .17; and when `affect` increases by 1, `withdraw` increases by .77.

So `estress` is increasing `affect` which is increasing `withdraw`.

```
## Call: mediate(y = withdraw ~ estress + (affect), data = estress)
##
## Direct effect estimates (traditional regression)    (c') X + M on Y
##            withdraw   se     t  df     Prob
## Intercept      1.45 0.25  5.74 259 2.61e-08
## estress       -0.08 0.05 -1.47 259 1.44e-01
## affect         0.77 0.10  7.46 259 1.29e-12
##
## R = 0.42 R2 = 0.18   F = 28.49 on 2 and 259 DF   p-value:  6.53e-12
##
##  Total effect estimates (c) (X on Y)
##            withdraw   se    t  df     Prob
## Intercept      2.06 0.26 7.87 260 9.64e-14
## estress        0.06 0.05 1.04 260 3.02e-01
##
##  'a'  effect estimates (X on M)
##            affect   se    t  df     Prob
## Intercept   0.80 0.14 5.58 260 6.11e-08
## estress     0.17 0.03 5.83 260 1.63e-08
##
##  'b'  effect estimates (M on Y controlling for X)
##         withdraw  se    t  df     Prob
## affect     0.77 0.1 7.46 259 1.29e-12
##
##  'ab'  effect estimates (through all  mediators)
##          withdraw boot   sd lower upper
```

```
## Call: mediate(y = withdraw ~ estress + (affect), data = estress)
##
## Direct effect estimates (traditional regression)    (c') X + M on Y
##            withdraw   se     t  df     Prob
## Intercept      1.45 0.25  5.74 259 2.61e-08
## estress       -0.08 0.05 -1.47 259 1.44e-01
## affect         0.77 0.10  7.46 259 1.29e-12
##
## R = 0.42 R2 = 0.18   F = 28.49 on 2 and 259 DF   p-value:  6.53e-12
##
##  Total effect estimates (c) (X on Y)
##            withdraw   se    t  df     Prob
## Intercept      2.06 0.26 7.87 260 9.64e-14
## estress        0.06 0.05 1.04 260 3.02e-01
##
##  'a'  effect estimates (X on M)
##            affect   se    t  df     Prob
## Intercept    0.80 0.14 5.58 260 6.11e-08
## estress      0.17 0.03 5.83 260 1.63e-08
##
##  'b'  effect estimates (M on Y controlling for X)
##         withdraw  se    t  df     Prob
## affect     0.77 0.1 7.46 259 1.29e-12
##
##  'ab'  effect estimates (through all  mediators)
##          withdraw boot   sd lower upper
```

Some final notes

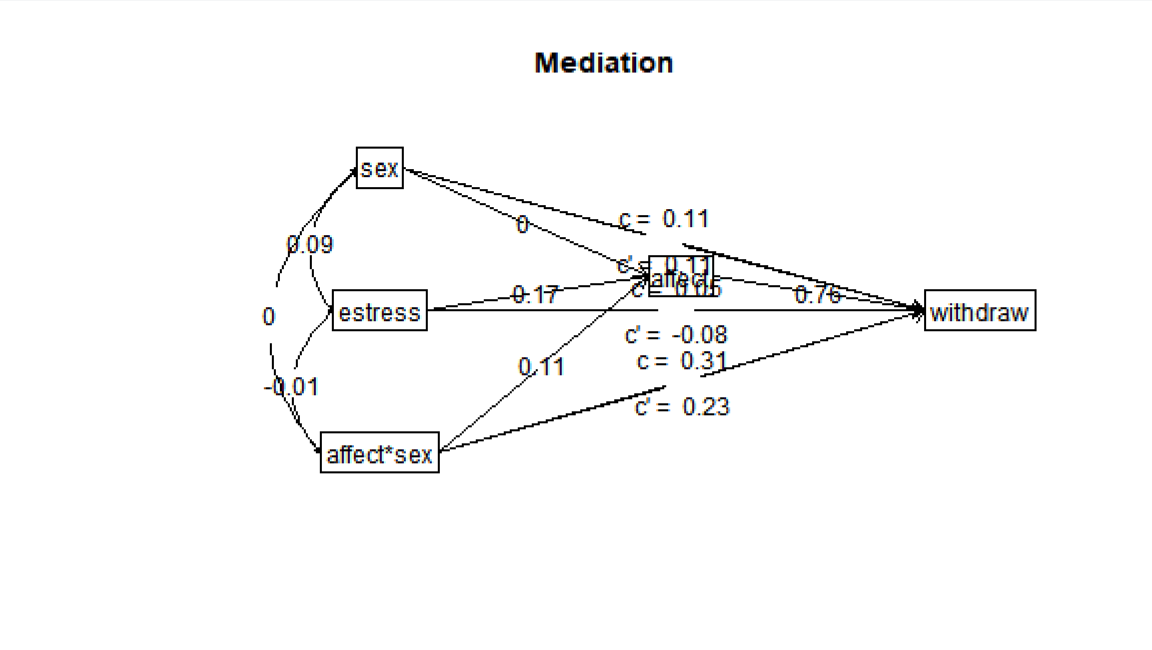
Multiple mediation

```
multi_medi <- mediate(withdraw ~ estress + (affect) + (tenure),
                      data = estress)
```

Moderated mediation

It's also possible to do *moderated mediation*. Simply include interaction terms for moderators. Have fun interpreting these 😈

```
mod_medi <- mediate(withdraw ~ estress + affect*sex + (affect),
                    data = estress)
```



Further reading

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 5, 1173-1182.*

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological Methods, 7, 422-445.*

Hayes AF. Introduction to mediation, moderation, and conditional process analysis: a regression-based approach. New York: Guilford Press; 2013.

Additional packages

The lavaan package for Structural Equation Modelling can be used to fit all sort of complicated models.

```
model <- ' # direct effect
             Y ~ c*X
           # mediator
             M ~ a*X
             Y ~ b*M
           # indirect effect (a*b)
             ab := a*b
           # total effect
             total := c + (a*b)
         '
fit <- sem(model, data = Data)
```

Additional packages

The `medmod` package can handle simple models, and has some nice, readable output.

```
library(medmod)
med_model <- med(data = estress, dep = "withdraw",
                 pred = "estress", med = "affect",
                 paths = TRUE, estPlot = TRUE,
                 pm = TRUE)
med_model$med
```

```
##
##  Mediation Estimates
##  ------------------------------------------------------------------------------------
##    Effect      Estimate       SE             Z             p            % Mediation
##  ------------------------------------------------------------------------------------
##    Indirect     0.13296411    0.02880709     4.615673    0.0000039       63.37328
##    Direct      -0.07684687    0.05209285    -1.475191    0.1401613       36.62672
##    Total        0.05611724    0.05399891     1.039229    0.2986982      100.00000
##  ------------------------------------------------------------------------------------
```

Mediation with `med()` from `medmod`

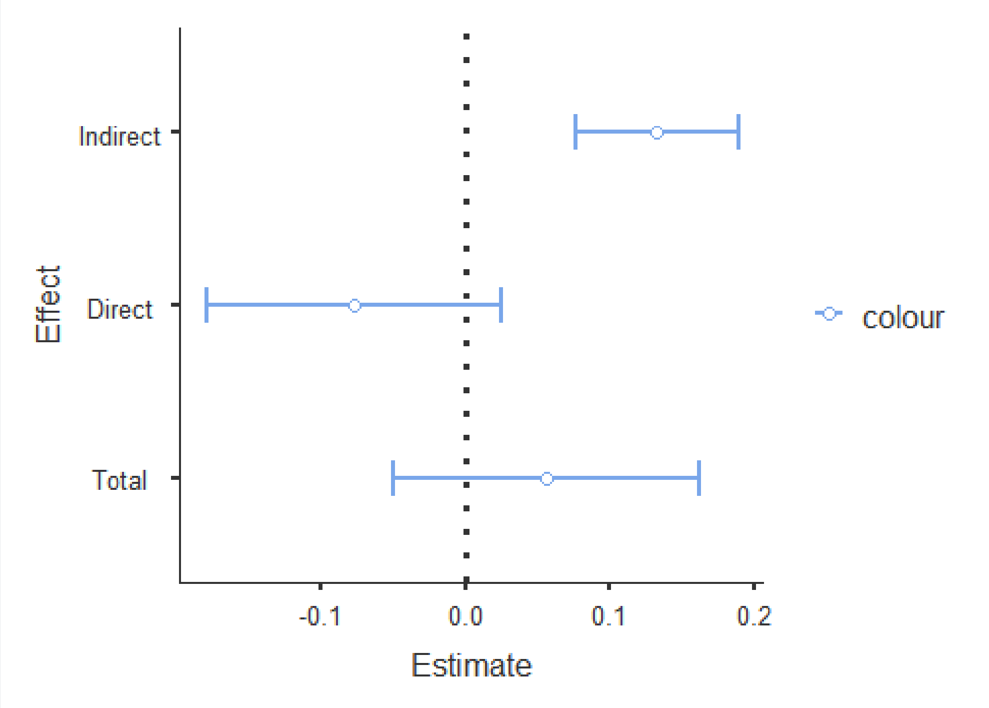
```
med_model$paths
```

```
##
##  Path Estimates
##  ------------------------------------------------------------------------------------
##                                        Estimate        SE            Z             p
##  ------------------------------------------------------------------------------------
##    estress    <U+2192>    affect         0.17287627    0.02953519     5.853230    < .0000001
##    affect     <U+2192>    withdraw       0.76912876    0.10247113     7.505809    < .0000001
##    estress    <U+2192>    withdraw      -0.07684687    0.05209285    -1.475191     0.1401613
##  ------------------------------------------------------------------------------------
```

PS this output looks better direct from R…!

Mediation with `med()` from `medmod`

```
med_model$estPlot
```



As long as the confidence intervals don't overlap 0 for the indirect effect, we have a significant mediation.